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In-Person Prehealth Advising: Impact Analysis Spring 2017 to Fall 2020

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In-Person Prehealth Advising

IMPACT ANALYSIS

SPRING 2017 - FALL 2020

Powered by Academic and Instructional Services

Report Presented September 2021

UtahStateUniversity

Exposure to In-Person Prehealth Advising Increases Student Persistence to the Next Term

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USU students who attended an in-person prehealth advising session experienced a significant increase in persistence to the next term compared to students who did not attend. The program help USU retain an estimated 37 at-risk students. That equals $168,135.77 in earned tuition attributable to this USU program.

ABSTRACT:

At Utah State University, some of the advising department's efforts specifically focus on preparing students for study in health professions graduate school. Students considering a career in the health sciences meet with an advisor who has been trained on the nuances of preparing for health professions graduate school.

This report explored the association between in-person prehealth advising participation and student persistence to the next term.

METHODS:

The Office of University and Exploratory Advising collected data about which attended advising, which advisor(s) they met with, and how many advising sessions they went to. Subsequent analysis compared students who participated in the in-person prehealth advising program to similar students who did not participate in the program.

Prediction-based propensity score matching (PPSM) was the method of student comparison. This technique matches students who participate in the program of inquiry with similar non-participant students. Two factors determine student similarity: (1) the students' computer-predicted level of academic persistence and (2) the students' propensity to participate.

FINDINGS:

Participant and comparison students were 99% similar after PPSM matching. Analysis used difference-in-difference testing to assess the advising program's impact. In the sample of 2,342 students, analysis found a significant positive correlation between program exposure and academic persistence (DID = 0.0156, p = 0.0132).

This equals 37 (CI: 8 to 65) students retained through this program, or $168,135.77 (CI: $36,353.68 to $295,373.65) in retained tuition.

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Does attendance at in-person prehealth advising sessions influence student persistence to the next term?

WHY PERSISTENCE?

Student success can be defined in various ways. One valuable way to view student success is through progress towards graduation. Progress towards graduation reflects students acquiring the necessary knowledge and accumulating credential that prepare them for graduation. The Center for Student Analytics measures progress towards graduation through the index measurement of student persistence. We define persistence as continuous semester-to-semester enrollment at Utah State University (e.g. fall-to-spring). As a measurement, persistence facilitates a quick feedback loop to identify what's working well and what can be better (Bear, Hagman, & Kil, 2020).

WHY USE ANALYTICS?

Higher education professionals labor to support student success in all its various forms--not just through persistence. However, professionals now have access to far more data than they can feasibly interpret and use to support student success without the help of analytics. Fortunately, USU has access to professional tools that can process and organize data into insights that have historically been hidden from view (Appendix A). University professions can leverage insights to directly influence student success (Baer, Kil, & Hagman, 2019). Indeed, analytics aligns with USU's mission to be a "premier student-centered land-grant institution." Analytics enables USU professionals to know what is going well and what could be better (see Appendix G for the evaluation cycle).

ACADEMIC ADVISING & PERSISTENCE

Academic advising enriches the university experience by increasing student exposure to several statistically-significant drivers of student persistence. These drivers include: "(1) student satisfaction with the college experience, (2) effective educational and career planning and decision making, (3) student utilization of campus support services, (4) student-faculty contact outside the classroom, and (5) student mentoring" (Cuseo, 2003).

USU prehealth advising makes a difference in undergraduates' lives by facilitating progress to graduation and smooth transitions to health professions graduate school.

Impact Analysis Results

SUMMARY STATISTICS

Overall Change in Persistence	1.56% (0.36% - 2.76%)
Overall Change in Students (per year)	37 (8 - 65)
Analysis Terms	Sp17, Su17, Fa17, Sp18, Su18, Fa18, Sp19, Su19, Fa19, Sp20, Su20, Fa20
Students Available for Analysis	2,342 Students
Students Matched for Analysis	2,342 Students
Percent of Available Students Matched for Analysis	100%
Percent of All Undergraduate Students Participating	8.07%

STUDENT IMPACT

Students who participate in in-person prehealth advising experience a significant increase in persistence to the next term. The estimated increase in persistence is equivalent to retaining 37 (CI: 8 – 65) students each year who were otherwise not expected to persist. This represents an estimated $168,135.77 (CI: $36,353.68 to $295,373.65) in retained tuition per year, assuming an average tuition of $4,544.21 (see Appendix C for estimated tuition table).

PARTICIPANT DEMOGRAPHICS

Matching procedures for this analysis resulted in the inclusion of 100% of available participants. Students were 66.52% male and 67.50% first-time college students. Analysis focused on undergraduate students.

PARTICIPANT POOL

The sample features USU undergraduate students from the Logan Main campus only. The sample excludes non-degree-seeking students, such as students pursuing certificates.

COMPARISON POOL

The comparison pool includes degree-seeking students from the Logan Main campus who were eligible to attend in-person prehealth advising sessions but did not choose to participate. Analysis used prediction-based propensity score matching methodology to identify comparison students. Comparison students must be similar to participants based on (1) their demographic and educational characteristics and (2) their likelihood to persist to the next semester.

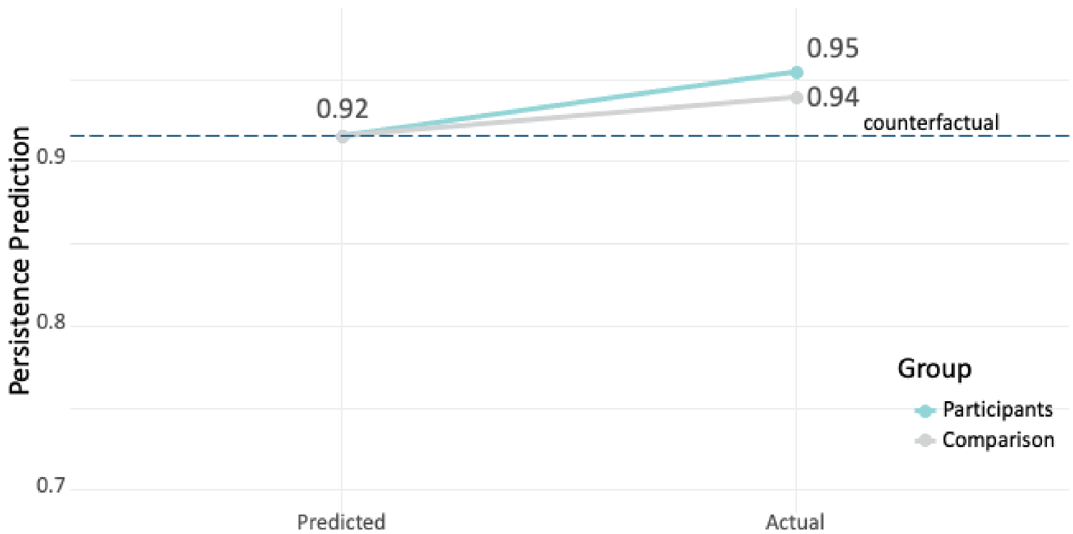

FIGURE 1. DEMONSTRATED PROGRAM IMPACT ON PERSISTENCE.

At the start of analysis, the pools of participant students and comparison students both have highly similar computer-predicted persistence scores. After analysis, differences emerge between the two groups in terms of their actual semester-to-semester persistence outcomes. What accounts for the difference between predicted vs. actual persistence outcomes for two otherwise highly similar pools of USU students?

Exposure--or no exposure--to the program of inquiry is the variable responsible for differences between the two groups. Prediction-based propensity score matching has successfully controlled for other confounding variables to isolate program exposure as a measurable independent variable.

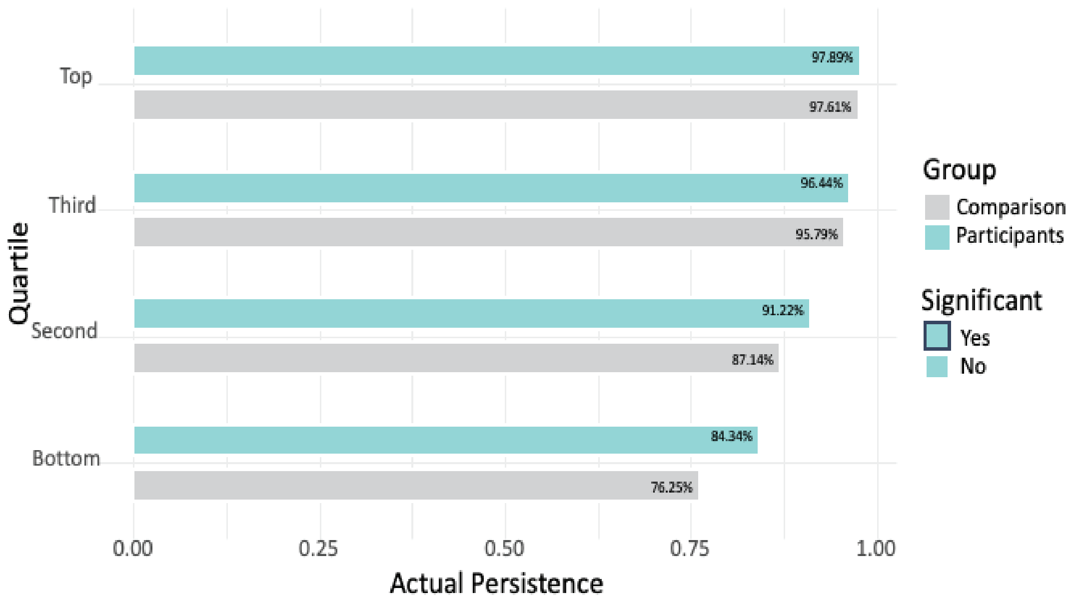

FIGURE 2
Actual persistence outcomes for students in each predicted persistence quartile.

Impact by Persistence Quartile

USU's predictive analytics model assigns each USU student a predicted persistence score--a measure of the student's likeliness to continue from one semester to the next in timely, unbroken progress.

Based on a student's prediction score, the student will belong to one of four persistence quartiles. Students in the top persistence quartile, for example, are the most likely to persist and make timely progress toward USU graduation. Students in the bottom persistence quartile are the least likely to persist from semester to semester. The participant pool and the comparison pool both include students from each predicted persistence quartile.

Although the in-person prehealth advising program demonstrates a statistically-significant impact on the overall USU student population, the data did not demonstrate a unique programmatic impact on one predicted persistence quartile (e.g. bottom quartile students) relative to the other quartiles.

Instead, analysis shows the in-person advising program to have a positive, statistically-significant impact spread across students in all four predicted persistence quartiles.

Impact by Term

Students have in-person prehealth advising services available to them year-round. Most students use the service in either the spring semester or the fall semester. Only a few students use the service during the summer. There tends to be a larger sample of students participating in in-person prehealth advising during fall than during spring.

Fall 2019 was the main semester that produced statistically-significant differences between the participant group's and the comparison group's persistence levels. Fall 2019 advising contributed to the retention of 12 (CI: 2 to 22) students not otherwise expected to persist. The remainder of significant impact spreads across multiple terms.

Decision-makers should bear in mind that the appearance of poor program persistence in certain semesters (e.g. summer 2017) is not statistically-significant.

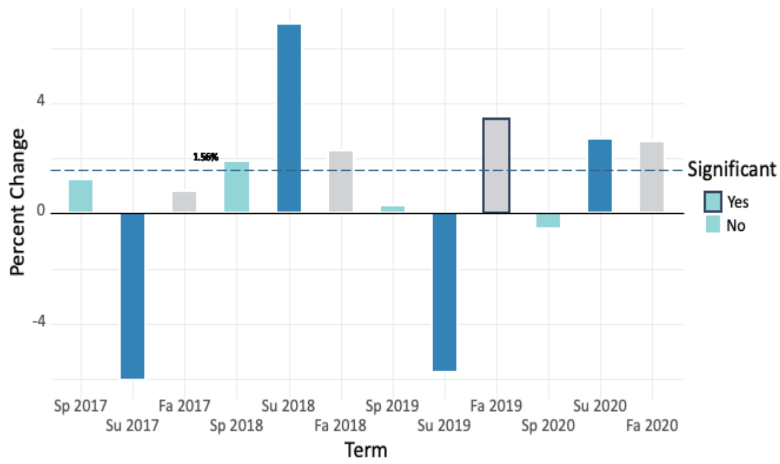

FIGURE 3
Term-by-term breakdown of the in-person prehealth advising program's impact on student persistence.

Student Segment Findings

IMPACTED STUDENT GROUPS

In addition to the holistic, bird's-eye view of programmatic impact that we have discussed so far, USU's predictive analytics software also provides insight about in-person prehealth advising's effect on specific segments and clusters of the student body. This section of the report explains the program's effect on some of these behavioral and demographic groups.

Please note that the student groups identified below are not mutually exclusive. Table 1 shows all student subgroups that experienced a significant change in persistence from their exposure to in-person prehealth advising. Appendix A lists all subgroups that did not experience significant change in persistence after exposure to advising.

In general, students who participated in in-person prehealth advising sessions experienced an increase in persistence. The following paragraphs present this program's impact on specific segments of the student body.

Degree Type (Figure 4). 54% percent of in-person prehealth advising participants were non-STEM majors, while about 46% were STEM majors. Results were statistically significant for non-STEM students in particular.

Non-STEM students experienced an above-average positive impact from the in-person advising program, relative to the overall advisee population. Non-STEM students who participated in advising experienced a 2.28% increase in persistence (CI: 0.48% to 4.08%).

Course Modality. USU students either take their classes all in-person, all online, or in a mix between in-person and online classes. 57% of the participant pool were students who take their classes in-person, 2% were all online, and 41% took a mix of in-person and online classes. Results were statistically-significant for students as a whole rather than for one course modality in particular.

Student Gender (Figure 5). Women represented 33% of the advisee participant pool, while men represented 67% of the pool. Results were statistically significant for women in particular.

Women who attended in-person prehealth advising sessions experienced positive effects from the program at an above-average rate compared to the overall participant pool impact. Women advisees experienced a 3.15% increase in persistence (CI: 0.95% to 5.35%).

Terms Completed. 17% of advisees were new students (0 terms completed), 35% were early career students (1 to 3 terms completed), and 48% were later career students (4 or more terms completed). Results were statistically significant for the pool of student advisees as a whole rather than for one particular "terms completed" subgroup of students.

Student Type. 68% of advisees were first-time college students, 14% were transfer students, and 18% were readmitted students. Results were statistically significant for first-time college students in particular.

First-time college students experienced an above-average positive effect from program exposure, relative to the overall advisee population. First-time students experienced a 2.39% increase in persistence (CI: 0.89% to 3.89%).

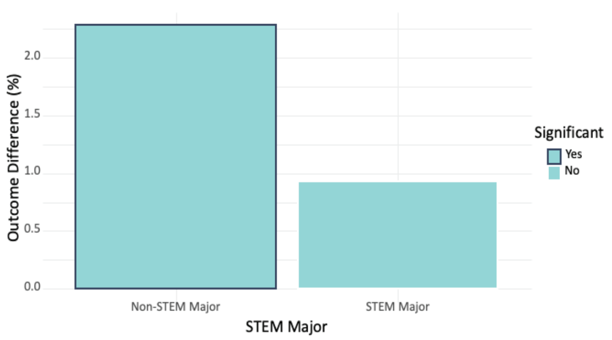

FIGURE 4

Changes in persistence for STEM major program participants vs. non-STEM major participants.

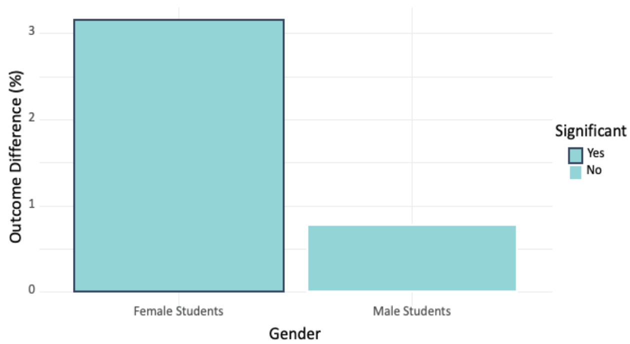

FIGURE 5

Changes in persistence, by gender.

Student Segment Table

TABLE 1:

Student Segments Experiencing a Significant Change In Persistence From Participating

N*	Student Group	Model Fit**	Participant Persistence	Comparison Persistence	Difference	CI	p-value	Lift in People
2,342	Overall	Adequate	95.44%	93.90%	1.56%	1.23%	0.0132	37
2,092	Full-time Courses	Adequate	96.08%	94.30%	1.79%	1.24%	0.0084	37
1,581	First Time in College	Adequate	96.23%	93.86%	2.39%	1.48%	0.0015	37
1,248	Non-STEM Major	Good	95.06%	92.80%	2.28%	1.83%	0.0148	28
774	Female Students	Good	96.10%	92.95%	3.15%	2.18%	0.0047	24

*Results may be less accurate for subgroups with fewer than 250 students

**Model fit refers to the degree to which the comparison is a reliable control group against which to compare the participants. A good comparison group will not deviate significantly from its predicted persistence outcomes. Good fit means there was a <1% difference between the comparison group's predicted persistence and its actual persistence outcomes. Adequate fit means the difference between predicted and actual persistence was between 1% and 2.9%. Poor fit indicates greater than 3% difference between actual and predicted persistence.

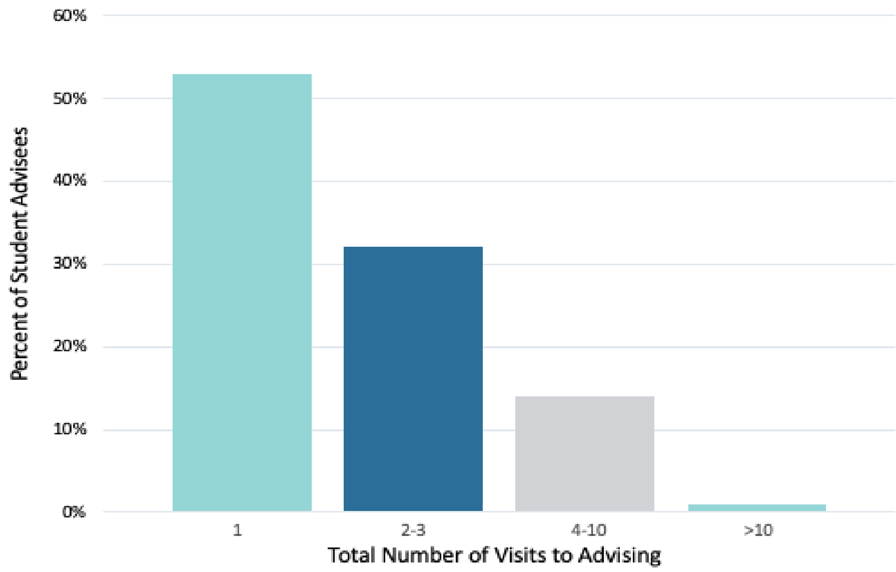

FIGURE 6

Relative rates of prehealth advising session attendance among students.

Additional Analyses

INVESTIGATING THE PROFILES OF STUDENTS WHO ATTEND ADVISING MORE THAN AVERAGE (>3 VISITS)

The data show that USU students vary in their habits of attending in-person prehealth advising. Some students attend advising as little as one time during their college careers, while some students attended advising at the maximum observed frequency: 19 visits. One additional investigation in this analysis tried to learn more about the motivations of the students who attend advising many times.

The typical prehealth advising student visits an advisor an average of 3.22 times or a median of 3 times. So, for the purposes of this investigation, analysis considered any student with more than 3 advising visits to have above-average visits.

Analysis compared the general prehealth advising population to the above-average visits population on six dimensions: age, GPA, earned credit hours, earned credit hours vs. attempted credit hours, total visit count, and visits-per-semester count.

Analysis did not reveal many dramatic differences between the general advising participant pool and the pool of participants with above-average visits. The subset of the advisee population with above-average visits was slightly older (average age: 22.17, median age: 22) than the total prehealth advisee population (average age: 21.46, median age: 21). Students with above-average frequency of advising visits also had a slightly higher number of earned credit hours (average: 86 credit hours) compared to the general prehealth advising population (average: 74 credit hours).

The median undergraduate student visits their prehealth advising officer 3 times.

ALL PREHEALTH ADVISEES

TABLE 2:	AVERAGE	MEDIAN
AGE	21.46	21
GPA	3.63	3.72
ATTEMPTED - EARNED HOURS	4.71	4
EARNED HOURS	74.36	70
TOTAL VISITS	3.39	3
VISITS PER SEMESTER	1.52	1

ADVISEES WITH >3 TOTAL VISITS

TABLE 3:	AVERAGE	MEDIAN
AGE	22.17	22
GPA	3.64	3.72
ATTEMPTED - EARNED HOURS	5.43	6
EARNED HOURS	86.06	84
TOTAL VISITS	5.98	5
VISITS PER SEMESTER	1.95	2

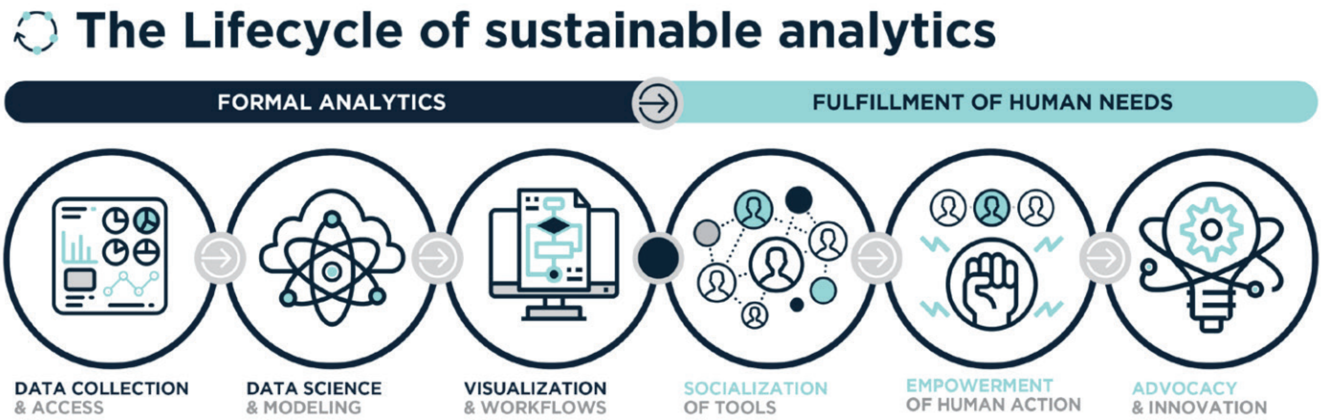

FIGURE 7

The Lifecycle of Sustainable Analytics.

Insights & Next Steps

Our analytics process combines a thorough evaluation of the data itself with an equally thorough reflection about the social and institutional context in which the data operates. We use the process visualized above in Figure 7--The Lifecycle of Sustainable Analytics--to transform insights from our data-gathering process into relatable, realistic themes that your department can work with as you begin to implement change. Here are some core conclusions we have identified during our collaborations with your department.

CREATING STRATEGIC SYNERGY BETWEEN ONLINE AND IN-PERSON PREHEALTH ADVISING

The Center for Student Analytics has completed analyses for both the online and the in-person versions of USU's prehealth advising program. Analysis in both cases reveals mostly good news. Both the online and the in-person prehealth advising initiatives demonstrate, within the range of statistical significance, a positive impact on USU student persistence.

The two programs are roughly parallel to each other in terms of the effect they have. In-person prehealth advising, as discussed earlier, contributes to the retention of about 37 students (CI: 8 to 65) whom we would not otherwise expect to persist from one term to the next. This leads to $168,135.77 (CI: $36,353.68 to $295.373.65) in retained tuition attributable to the in-person advisors. Online prehealth advising's performance is right on par with in-person advising. Online advising retains 33 students (CI: 11 to 56), or $148,958.93 (CI: $49,986.31 - $254,475.76).

When two similar programs perform at roughly the same level, there is an opportunity to create synergy between the two programs' operations. Are there students who end up in online advising who might be better served in-person, and vice versa? How should pandemic-related adaptation concerns influence the distribution of online vs. in-person advising?

DELEGATING ADVISING ROLES

At the time of this analysis, USU has two staffers assigned to in-person advising responsibilities. However, the data show that up to nine different staffers have held in-person prehealth advising responsibilities during the 2017-2020 period. The two current in-person advisors do not have significant differences in the statistical profiles of their advisee students, but the nine historical advisors as a whole do have larger differences between their student profiles. There is room for strategic planning about which prehealth students get assigned to which advisor--and why.

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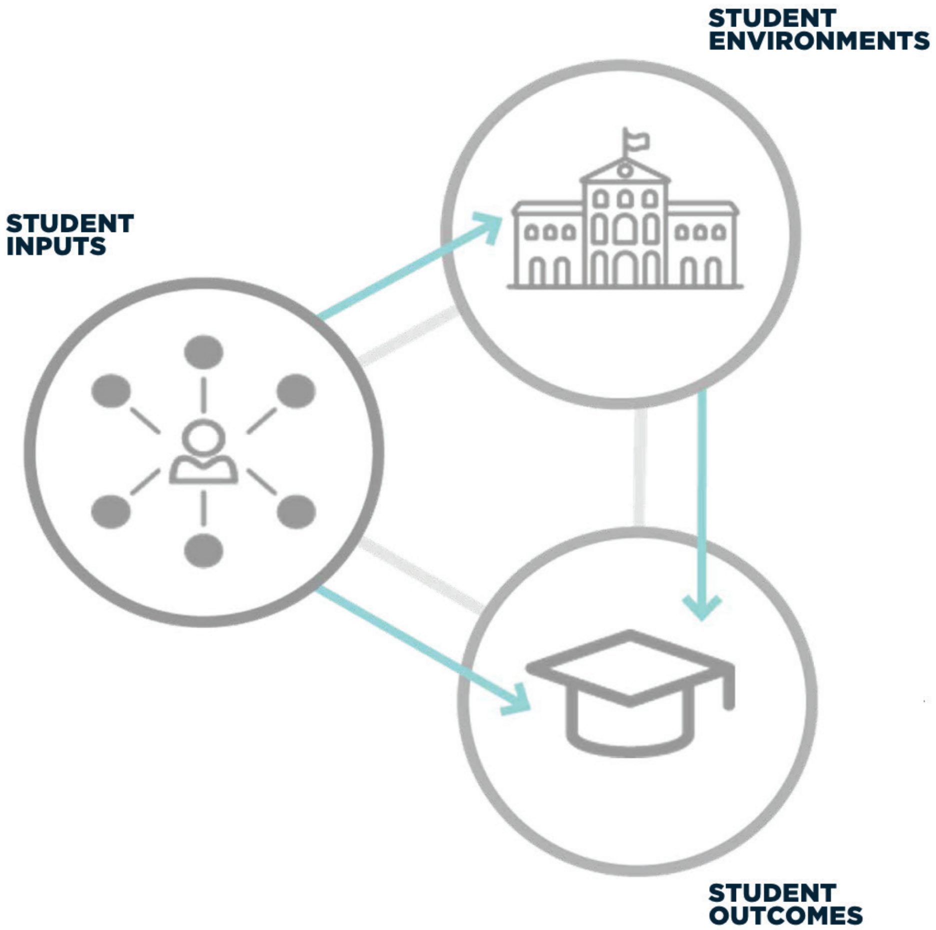
Appendix A

THEORETICAL FOUNDATION FOR IMPACT ANALYSES: INPUT, ENVIRONMENT, OUTPUT MODEL (ASTIN, 1993)



Input - Environment - Outcomes

Student success occurs through the combination of two sets of variables: student input and environmental influence (Astin, 1993). Our prediction-based propensity score matching methodology controls for student input variations by matching participant students with similar non-participant students based on their: (1) likelihood to be involved in an environment and (2) their predicted persistence score. By controlling for student inputs, we isolate environmental influence--program exposure--as the independent variable of study.

STUDENT INPUTS

Students bring different combinations of strengths to their university experience. Student input influences student success, but it does not by itself determine the outcomes.

STUDENT ENVIRONMENTS

A university provides a diverse array of curricular, co-curricular, and extra-curricular activities to enhance the student experience. Students selectively participate to varying degrees in activities. The student's learning environment influences student success, but it does not by themselves determine these outcomes.

STUDENT OUTCOMES

There are several ways to measure student success. We have chosen persistence as our index measurement of student success. Persistence is continuous enrollment from one semester to the next; it is timely progress toward graduation. The interaction of student inputs and student environments is what determines student persistence.

PPSM IMPACT ANALYSIS

A prediction-based propensity score matching impact analysis can effectively measure university programs' effect on student persistence. It does so by treating student inputs as a control variable, so as to isolate student environments as the independent variable of study.

Appendix B

ANALYTIC DETAILS: ESTIMATING PROGRAMMATIC IMPACT THROUGH PREDICTION-BASED PROPENSITY SCORE MATCHING (PPSM)

Impact analyses are quasi-experiments that compare students who participate in University initiatives to similar students who do not. In an impact analysis, "participants" are students who participate in the program of inquiry. "Comparison students" are similar to participants in profile and behavior, except for participation in the program of inquiry. An impact analysis estimates the effect of the treatment on the treated (ETT). In other words, our analysis estimates how exposure to a student success program affects student persistence outcomes. Such estimations are most appropriate for observational studies with voluntary participation (Geneletti & Dawid, 2011).

Accounting for bias. While ETT is fitting for observational studies with voluntary participation, the phenomenon of voluntary participation introduces the problem of bias. Specifically, students' voluntary participation in a program results in self-selection bias, where the distinction between participants and non-participants follows natural differences in student profile and behavioral history. Participant students and non-participant students may be innately different from each other. For example, students who self-select into math tutoring (or intramurals or the Harry Potter Club) may be quantitatively and qualitatively different than students who do not use math tutoring (or intramurals or the Harry Potter Club). Prediction-based propensity score matching (PPSM) is a way to account for these differences, reduce the effect of self-selection bias, and increase the validity of an impact analysis.

In PPSM, the matching process pairs participating students with non-participating students who are similar to them in both their (a) predicted persistence and (b) their propensity to participate in an iterative, boot-strapped analysis (Milliron, Kil, Malcolm, & Gee, 2017).

(A) Predicted Persistence. Utah State University uses student data to create a persistence prediction score for each student. The persistence prediction score system serves as an early alert system. It identifies students who may need supplemental resources to support their success at USU. These persistence prediction scores also help our data analysts and data scientists evaluate student-facing programs' impact on student success. Assessment and evaluation are invaluable practices that foster accountability, efficiency, and innovation in university operations.

A regularized ridge regression model generates the prediction scores, evaluating such student data points as including:

- academic performance;
- degree progress metrics;
- socioeconomic status; and,
- student engagement.

The ridge regression ranking orders each covariate by its predictive power, and the resulting equation generates the persistence prediction score. We match participants with non-participants whose prediction scores are similar to theirs.

(B) Propensity to Participate. Propensity scores, another data point used for PPSM matching, reflect a students likelihood to participate in an initiative (Rosenbaum & Rubin, 1983). A logistic ridge regression modeling process predicts a student's statistical likelihood to participate in the program of inquiry.

Matching proceeds through bootstrapped iterations that randomly select a subset of participant and comparison students. Within each bootstrapped iteration, we match participants with similar non-participants using 1-to-1, nearest neighbor matching. To match, two students' persistence and propensity scores must fall within a 0.05 caliper width of each other. The random bootstrapping iterations examine each participant for matching. They ultimately exclude from analysis are any participant students who do not find an adequate match. (For additional details, see Louviere, 2020).

Difference-in-Difference. Difference-in-difference analysis compares participant outcomes to comparison outcomes by comparing the calculated predicted means from the bootstrapped iteration distributions to the actual persistence rates of participating and comparison students. In other words, the analysis looks at the difference between predicted persistence and actual persistence between the two groups of well-matched students. We treat results with alpha <0.05 as statistically significant within a 95% confidence interval. The results finally display the ETT.

Appendix C

ADJUSTED RETAINED TUITION MULTIPLIER

Retained tuition equals the number of retained students multiplied by the USU average adjusted tuition. The numbers in the tuition table below reflect information provided by the USU Budget and Planning Office about tuition rates for the 2018-2019 academic year.

The amounts in the table reflect net tuition--an estimate of tuition that removes all tuition waivers from the overall gross tuition amounts. This net tuition calculation provides a more accurate and more conservative multiplier for understanding the impact of university initiatives on retained tuition.

The table below parses the average adjusted tuition by campus and academic level. The highlighted row indicates the multiplier we used in this analysis.

TABLE 4:
RETAINED TUITION MULTIPLIER CALCULATION

Student Groups	Net Tuition	Number of Students	Average Annual Tuition & Fees
All USU Students	$148,864,384	33,070	$4,501.49
Undergraduates	$131,932,035	29,033	$4,544.21
Graduates	$16,932,349	4,037	$4,194.29
Logan Campus Students	$119,051,003	25,106	$4,741.93
Undergraduates	$107,711,149	22,659	$4,753.57
Graduates	$11,339,854	2,447	$4,634.19
STATE-WIDE CAMPUS STUDENTS	$25,941,419	7,964	$3,257.34
Undergraduates	$20,303,215	3,864	$5,254.46
Graduates	$5,638,204	1,590	$3,546.04
USU-E Price & Blanding Students	$3,871,962	2,560	$1,512.49

Appendix D

STUDENT SEGMENTS THAT DID NOT EXPERIENCE A SIGNIFICANT CHANGE IN PERSISTENCE

TABLE 5:

Student Segments That Did Not Experience a Significant Change In Persistence From Participating

		Actual Persistence				
N*	Student Segment**	Participants	Comparison Students	Difference-in-Difference	CI	p-value
1,558	Male Students	95.12%	94.36%	0.78%	1.50%	0.3052
1,344	All On-Ground Status	95.23%	93.69%	1.56%	1.64%	0.0625
1,123	4+ Terms Completed	97.24%	96.14%	1.11%	1.45%	0.1341
1,077	Top Persistence Prediction Quartile (75th-100th Percentile)	97.89%	97.61%	0.28%	1.25%	0.6591
948	Mixed or Blended Status	95.77%	94.17%	1.61%	1.93%	0.1024
817	1-3 Terms Completed	93.65%	92.27%	1.40%	2.39%	0.2498
710	Third Persistence Prediction Quartile (50th-74th Percentile)	96.44%	95.79%	0.66%	2.01%	0.5179
415	Readmitted Students	95.32%	95.75%	-0.42%	2.69%	0.7603
398	0 Terms Completed	94.08%	90.99%	3.09%	3.39%	0.074
395	Second Persistence Prediction Quartile (25th-49th Percentile)	91.22%	87.14%	4.11%	4.28%	0.06
325	Transfer Students	93.71%	93.36%	0.35%	3.69%	0.8511
153	Bottom Persistence Prediction Quartile (1st-24th Percentile)	84.34%	76.25%	8.13%	8.26%	0.0539
48	All Online Status	95.36%	94.38%	1.03%	8.06%	0.8008

*Results may be less accurate for subgroups with fewer than 250 students
**Student group definitions available in appendix F

Appendix E

MATCHING DETAILS

Following prediction-based propensity score matching process described in Appendix B, we were able to match 100% of available participants, or 2,342 students. As a rule, we exclude from analysis any participating students who do not have an appropriate profile/behavior match in the pool of non-participants.

Upon reviewing the matching distributions for predicted persistence (Figure 8) and for propensity to participate (Figure 9), the reader will see that there is substantial overlap between the red and blue lines. This overlap indicates high similarity of profile and behavior between each caliper-pair of students in the participant pool and the comparison pool.

Prior to matching, the participant and comparison students were 82% similar based on students' predicted persistence (Figure 8) and 69% similar based on students' propensity to participate in the in-person prehealth advising program (Figure 9). Following matching, the participant and comparison pools were 99% similar and 98% similar, respectively.

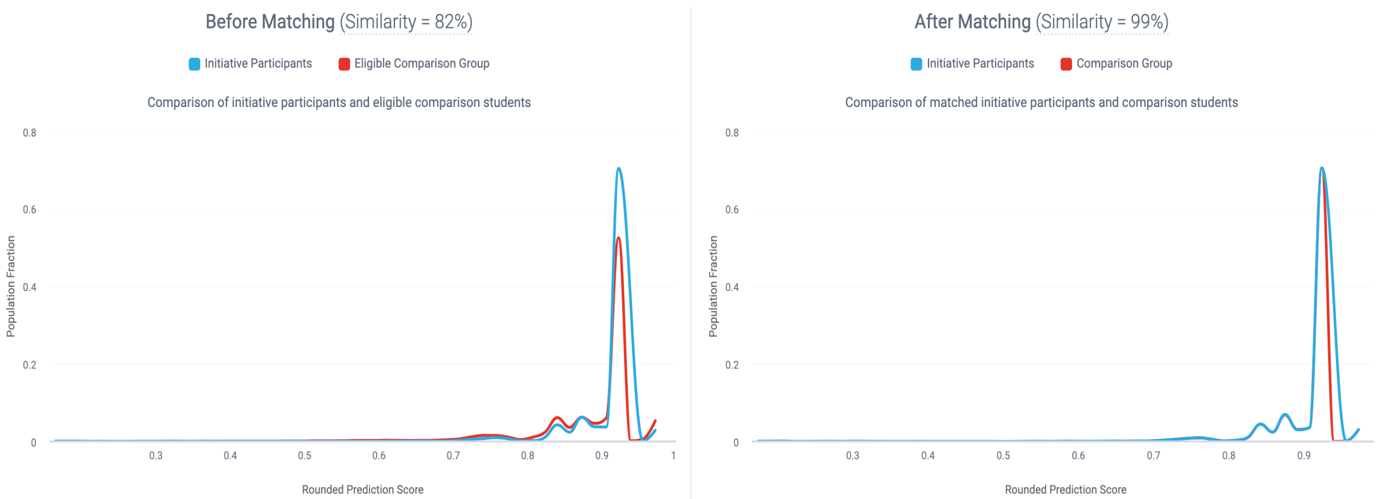


FIGURE 8. PREDICTION-BASED PROPENSITY SCORE MATCHING: PREDICTED PERSISTENCE

Participating and comparison students receive prediction persistence scores based on their regression-predicted persistence to the next semester. We run the regression based on the most recent four years of USU student performance data.

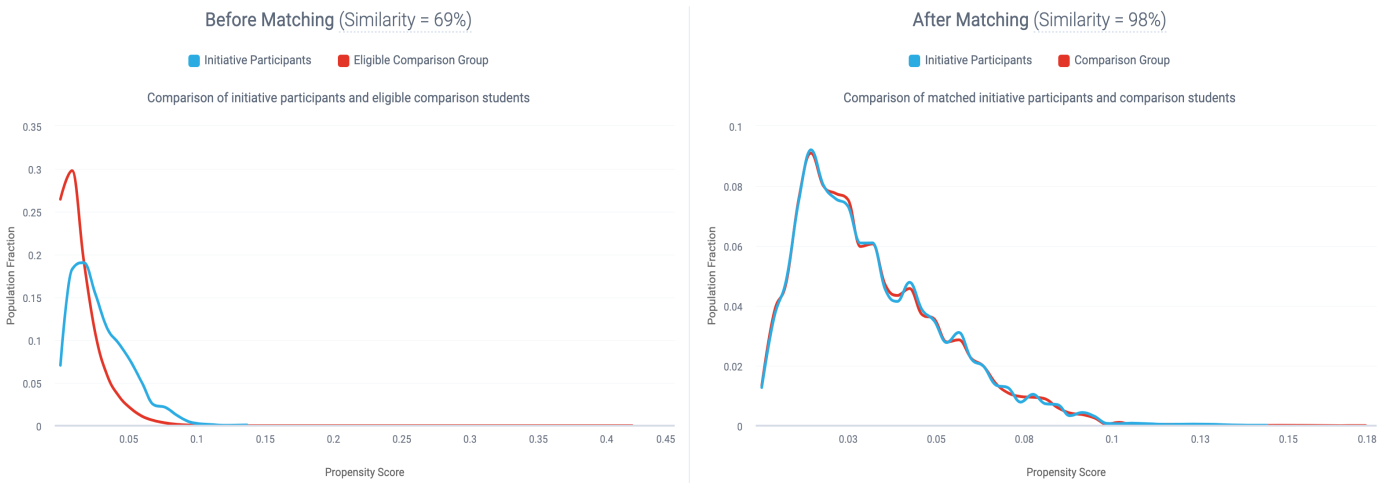


FIGURE 9. PREDICTION-BASED PROPENSITY SCORE MATCHING: PROPENSITY FOR PROGRAM PARTICIPATION

Participating and comparison students receive regression-predicted propensity scores based on their likelihood to participate in the in-person prehealth advising program. We run the regression using the most recent four years of USU student data.

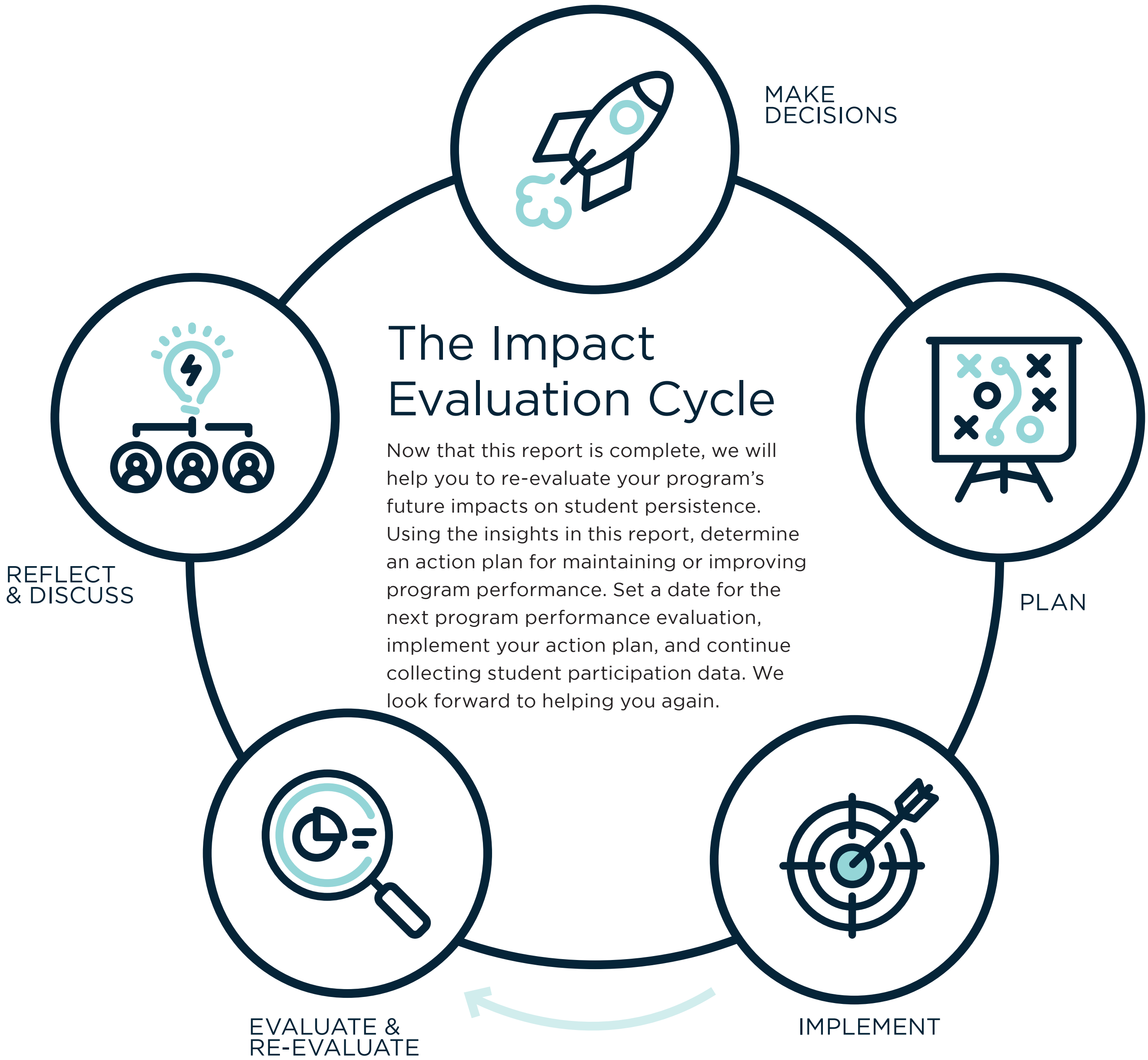
Appendix F

STUDENT SEGMENT DEFINITIONS

Student Subgroup	Definition
0 Terms Completed	Students with 0 terms in their collegiate career completed; incoming freshmen
1 - 3 Terms Completed	Students who have completed 1 to 3 terms in their collegiate career
4+ Terms Completed	Students with 4 or more terms in their collegiate career completed
All On-Campus	Students attending all courses face-to-face
Online or Broadcast	Students attending all courses online or via broadcast
Mixed or Blended Course Modality	Students attending both face-to-face and online or broadcast courses
Full-time Students	Undergraduate students enrolled in 12 or more credits
Part-time Students	Undergraduate students enrolled in less than 12 credits
First Time in College	Students who enter USU as new freshmen
Transfer Students	Students who attended another university prior to attending USU
Readmitted Students	Students who attended USU, left for a time (without filing a leave of absence), and return after re-applying to USU
Unknown Undergraduate Type	Students with an unknown admitted type
High School Dual Enrollment	High school students simultaneously taking high school and college courses
STEM	Students with a primary major in science, technology, engineering, or mathematics
Non-STEM	Students with a primary major that is not in science, technology, engineering, or mathematics
Top Persistence Prediction Quartile	25% of the total USU population falls into each quartile. The top quartile contains students with the highest predicted persistence (75th – 100th percentile)
Third Persistence Prediction Quartile	25% of the total USU population falls into each quartile. The third quartile contains students with the second-highest predicted persistence (50th – 74th percentiles)
Second Persistence Quartile	25% of the total USU population falls into each quartile. The second quartile contains students with the second-lowest predicted persistence (25th – 49th percentiles)
Bottom Persistence Quartile	25% of the total USU population falls into each quartile. The bottom quartile contains students with the lowest predicted persistence (1st – 24th percentile students)
Female	Students identifying as women
Male	Students identifying as men

Appendix G

THE USU CENTER FOR STUDENT ANALYTICS EVALUATION CYCLE



The Impact Evaluation Cycle

Now that this report is complete, we will help you to re-evaluate your program's future impacts on student persistence. Using the insights in this report, determine an action plan for maintaining or improving program performance. Set a date for the next program performance evaluation, implement your action plan, and continue collecting student participation data. We look forward to helping you again.

EVALUATE & RE-EVALUATE

Submit program participation data to the Center for Student Analytics, and we will run an evaluation. We can help you study persistence outcomes or help you find other ways to measure performance.

REFLECT & DISCUSS

Consider the insights in your impact evaluation report and have a discussion within your department about the key themes of the report.

MAKE DECISIONS

Brainstorm possible strategies for maintaining or improving your program's impact on USU student success. Aim for outcomes that align with your program's goals.

PLAN

Make a realistic action plan for implementing your strategic decisions. Determine the "who," the "where," and the "when" of your actions.

IMPLEMENT

Put your plans into action. Remember to collect participation data and periodically check the progress of your plans as they are being implemented.